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Informativeness of Performance Measures: Coefficients or R-Squareds?

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Abstract: Measuring the informativeness of earnings is of fundamental importance to accounting research. Both coefficients and R-squareds have been proposed as candidates for measuring the informativeness of earnings. However, recent research has focused substantially more on using coefficients, rather than R-squareds, to draw inferences. This paper first documents in a small theoretical model that under some circumstances, R-squareds map more closely to informativeness than coefficients. Second, this paper documents that in archival data, coefficients and R-squareds can draw opposite inferences regarding the informativeness of earnings and other performance measures up to 50% of the time. Third, this paper proposes an approach to provide statistical inference using R-squareds. Taken together, this paper suggests that rather than solely relying on coefficients, as is common in prior literature, R-squareds can also be used to measure the informativeness of earnings and other performance measures.

Keywords: earnings response coefficients; earnings–return relation; capital markets; financial accounting; earnings announcements

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1. Introduction

Measuring the informativeness of earnings is of fundamental importance to accounting research. Such measures, commonly referred to as earnings response coefficients (ERCs), have been widely used to draw inferences on topics ranging from audit to governance quality to earnings management (Dechow et al. 2010).[1] In the literature, both coefficients and R-squareds have been proposed as candidates to measure the informativeness of earnings (Greene 2018). However, recent research has focused substantially more on coefficients than R-squareds. This paper proceeds in three steps. First, this paper illustrates the conceptual difference between R-squareds and coefficients using a small theoretical model and shows that that under some circumstances, R-squareds have a closer mapping to earnings informativeness than coefficients. Second, this paper documents using archival data that R-squareds and coefficients can draw opposite inferences about the informativeness of earnings and other performance measures and, in some cases, up to 50% of the time. Finally, this paper proposes a methodology to estimate two-way cluster robust standard errors for R-squareds, which permits statistical inferences to be made about R-squareds in future applications.

This paper begins by illustrating the conceptual difference between R-squareds and coefficients in measuring earnings informativeness using a small theoretical model. Intuitively, it is possible for coefficients and R-squareds to draw opposite inferences because they capture different aspects of a firm's valuation. For example, for an industry with a high price–earnings ratio, the coefficient may be high because an additional unit of earnings translates into incrementally higher prices on average (e.g., Kothari and Zimmerman 1995). However, firms in industries with high price–earnings ratios may not necessarily have informative earnings, for example, because fundamentals are driven by other performance measures (e.g., Sloan 1996). Thus, it is possible for firms with low earnings informativeness to have high coefficients in ERC regressions. In contrast to coefficients, R-squareds directly measure the proportion of variance in returns explained by earnings. In other words, the R-squared is a type of signal-to-noise ratio that can potentially be a valid measure of the informativeness of earnings (e.g., Lambert and Larcker 1987). This paper formalizes this intuition in a small theoretical model.

The main idea of the model is that in a mean-variance framework, an investor prefers payoffs with lower variance, all else being equal. Thus, the value of a signal, such as earnings, is directly related to its ability to reduce the variance of the final payoff, such as the future firm value or future cash flows, conditional on the value of the signal. This paper shows that under this framework, the R-squared of a payoff (e.g., returns) regressed on a signal (e.g., earnings surprise) directly captures the variance reduction in the payoff conditional on the signal. In addition, the R-squared value is invariant to arbitrary scaling of the signal (e.g., multiplying the signal value by 2). In contrast, the coefficient on the signal in the regression varies according to arbitrary scaling and can sometimes draw opposite conclusions as the R-squared value. In other words, for two signals A and B, it is possible for the coefficient on signal A to be larger than the coefficient on signal B when the R-squared for signal A is smaller than the R-squared for signal B. However, in all cases, the R-squared value aligns with the amount of variance reduction in the payoff conditional on the signal. Thus, R-squareds map more closely to informativeness in a mean-variance framework. This paper then confirms the predictions of the theoretical model with simulated data.

Next, this paper documents the extent to which coefficients and R-squareds draw opposite inferences in archival data. This is important because although coefficients and R-squareds could draw opposite inferences theoretically, the extent to which this occurs in archival data is not known. The archival tests begin with comparing coefficients and R-squareds across Fama–French 48 industries. This corresponds to the empirical question of whether earnings are more informative in certain industries than in other industries. Although the coefficient measure is standardized in the literature, there is less standardization of the R-squared measure. Thus, this paper examines four different R-squared measures that have potential theoretical appeal: R-squared, adjusted R-squared, incremental R-squared, and incremental adjusted R-squared. In sum, this paper compares the inferences drawn by five candidate measures.

This paper also estimates specifications with and without controls. For the without controls specification, this paper regresses earnings announcement period returns on earnings surprises. For the controls specification, return on assets, size, book to market, revenue, cash flows from operations, revenue surprises, and cash flows from operations surprises are included as controls. The measure of the extent to which coefficients and R-squareds draw opposite inferences regarding the informativeness of earnings is *Disagreement*, the average percentage of the time that two measures being compared draw opposite inferences regarding the informativeness of earnings for two different Fama–French 48 industries. This paper also examines revenue surprises and cash flows from operations surprises in addition to earnings surprises because of the increasing focus on performance measures that are alternatives to earnings (e.g., Sloan 1996; Jegadeesh and Livnat 2006).

In the specification without controls, this paper finds that coefficients and the various R-squared measures draw opposite inferences 14.9–15.3 percent of the time. For revenue surprises and cash flows from operations surprises, coefficients and the various R-squared measures draw opposite inferences 14.7–16.6 percent and 19.8–20.2 percent of the time, respectively. This suggests that there is a non-trivial percentage of cases in which coefficients and R-squareds draw opposite inferences regarding the informativeness of earnings and other performance measures for different industries. This is important because it suggests that for up to 20 percent of all comparisons across industries, coefficients and R-squareds draw opposite conclusions about the informativeness of earnings, revenues, and cash flows.

In the specification with controls, the divergence between coefficients and R-squareds is even greater. For earnings surprises, coefficients and R-squareds draw opposite inferences 13.3–42.6 percent of the time. For revenue surprises and cash flows from operations surprises, coefficients and R-squareds draw opposite inferences 22.0–48.8 percent and 46.8–56.7 percent of the time, respectively. Thus, when controls are included, in some cases, it is possible for coefficients and R-squareds to draw opposite conclusions about earnings and other performance measures up to and around 50 percent of the time. These findings suggest that coefficients and R-squareds can draw opposite inferences for a substantial proportion of cases in certain archival settings. Combined with the theoretical model intuition that R-squareds can more closely map to informativeness than coefficients under certain frameworks, this paper suggests not solely relying on coefficients and also considering R-squareds as an additional candidate to assess the informativeness of earnings.

In the final part of this paper, this paper proposes a method to estimate standard errors for R-squareds. This is important because standard errors are a standard for inferences in accounting and finance research. This task is made more challenging because of the necessity of considering two-way cluster robust standard errors in standard panel data in accounting and finance research. Whereas there has been substantial research on and application of the calculation of two-way cluster robust standard errors for coefficients, there is far less such research and application for R-squareds. This paper proposes an estimation methodology based on bootstrapping. This paper first validates that bootstrapped standard errors for coefficients are similar to standard errors calculated using the standard analytical approach and then presents the methodology and findings for R-squareds.

This paper contributes to the literature in three ways. First, this paper provides a conceptual illustration of how coefficients and R-squareds can be different in the context of measuring the informativeness of earnings. It shows that under some circumstances, R-squareds map more closely to informativeness than coefficients. Although most archival research focuses on coefficients, this paper suggests that R-squareds can be an important metric in assessing the informativeness of earnings and other performance measures.

Second, this paper documents the extent to which coefficients and R-squareds can provide different inferences. Because most recent literature uses coefficients and not R-squareds to draw inferences, the extent to which coefficients and R-squareds can provide different inferences is largely unknown. This paper documents that coefficients and R-squareds can draw opposite inferences up to 50 percent of the time in certain archival settings. Thus, this paper documents that examining R-squareds can provide substantially different results from examining coefficients. Future research may consider examining both coefficients and R-squareds in assessing the informativeness of earnings and other performance measures.

Finally, this paper proposes an approach for estimating two-way cluster robust standard errors for R-squareds. Whereas there has been substantial research on and application of the calculation of two-way cluster robust standard errors for coefficients, there is far less such research and application for R-squareds. Thus, this approach could help future research to provide statistical inferences regarding R-squareds.

This paper is not suggesting that all future research should focus on R-squareds to the exclusion of coefficients. Rather, this paper suggests that in addition to coefficients, R-squareds could be considered as an additional candidate to measure the informativeness of earnings and other performance measures. If coefficients and R-squareds draw opposite inferences regarding the informativeness of a performance measure in a particular setting, such a disagreement may warrant a more careful examination of the inference.

This paper does not resolve other longstanding debates on ERCs, such as developing the correct earnings expectation and the correct functional form. In other words, this paper does not provide a solution regarding the correct expectation for earnings or the correct functional form of the ERC. Although this paper does not provide solutions regarding these issues, the findings in this paper can potentially be complementary to solutions regarding these issues. For example, given a more accurate proxy for earnings expectations, the idea that R-squareds can be used to assess the informativeness of earnings can still be applied in conjunction with the more accurate earnings expectations. Similarly, given a more appropriate functional form, R-squareds can be used to assess the informativeness of earnings, especially when coefficients may not be well-defined under certain functional forms. An example of this could be a functional form that includes both a linear term and a squared term for earnings. Comparing coefficients across two industries or other subsample types may be more difficult than in a specification with only a linear term. For example, examining coefficients could be inconclusive if one industry has a larger coefficient on the linear term but a smaller coefficient on the squared term. In contrast, the (incremental) R-squared is a single value that captures the (incremental) explanatory power of both terms.

Section 2 discusses the background and develops the model. Section 3 presents the empirical research design. Section 4 describes the sample and data. Section 5 presents the findings. Section 6 proposes the approach to estimate standard errors for R-squareds. Section 7 concludes.

2. Model and Background

2.1. Model of Conceptual Differences Between Coefficients and R-Squareds

Because regression coefficients and R-squareds do not measure the same quantity, it is possible for them to be different. In fact, they will not be equal to each other in general. In linear regression, the coefficient measures the relation between the outcome and the independent variable of interest, whereas the R-squared measures the strength of the fit (Greene 2018). Coefficients are more useful for the interpretation of the relationship between variables, whereas R-squareds focus on the goodness of fit of the empirical model.

In a standard accounting and finance context, a risk-averse investor with mean-variance preferences has a greater preference for higher mean returns and lower variances (Huang and Litzenberger 1988). Lower variances directly map to R-squared but not directly to coefficients. This paper illustrates using a small theoretical model below in which R-squared maps directly to informativeness, whereas coefficients do not. The main intuition is that coefficients can be arbitrary based on the scaling of independent variables, whereas R-squared values are invariant to the scaling of independent variables.

Consider an investor with mean-variance preferences with risk aversion coefficient A. The investor's utility over a particular portfolio P is $\mathrm{E}[P] - 0.5 \times A \times \mathrm{Var}(P)$ (Huang and Litzenberger 1988). Consider an investor of an asset X with the following payoff:

$$X = u + e$$

as well as two signals Y or Z with values given by

$$Y = u + d$$

$$Z = 2 \times Y$$

where

$$u \sim \mathrm{N}(\mu, {\sigma_\mu}^2)$$

$$e \sim \mathrm{N}(0, {\sigma_e}^2)$$

$$d \sim \mathrm{N}(0, {\sigma_d}^2)$$

and u, e, and d are independent. Intuitively, both Y and Z provide information about the realization of u with noise, which is informative to an investor of X. In fact, Z provides the exact same information as Y because the realization of Z is simply double the value of the realization of Y. Writing out the distributions more fully:

$$X \sim \mathrm{N}(\mu, {\sigma_\mu}^2 + {\sigma_e}^2)$$

$$Y \sim \mathrm{N}(\mu, {\sigma_\mu}^2 + {\sigma_d}^2)$$

$$Z \sim \mathrm{N}(2\mu, 4\sigma_\mu{}^2 + 4\sigma_d{}^2)$$

Also, for notational simplicity, let $\sigma_X{}^2 = \sigma_\mu{}^2 + \sigma_e{}^2$, $\sigma_Y{}^2 = \sigma_\mu{}^2 + \sigma_d{}^2$, and $\sigma_Z{}^2 = 4\sigma_\mu{}^2 + 4\sigma_d{}^2$.

Now, consider an investor of X that learns about the realization of Y. This could be motivated by X being future profit, firm value, or another quantity the investor cares about and Y being current earnings or another performance measure that the investor learns. Because Y reveals u with noise, an investor of X that learns the realization of Y will update beliefs about the distribution of X because Y contains information about the realization of u. For an investor of X that learns the value of Y, the expected value and variance of X is as follows:

$$\mathrm{E}[X \mid Y = y] = \mu + \rho_{XY}\, \sigma_X/\sigma_Y\, (y - \mu)$$

$$\mathrm{Var}(X \mid Y = y) = \sigma_X{}^2(1 - \rho_{XY}{}^2)$$

where $\rho_{XY} = \sigma_\mu{}^2/\sigma_X\sigma_Y$ is the correlation between X and Y.

Now, for an investor that only learns about the value of Z, the expected value and variance of X is as follows:

$$\mathrm{E}[X \mid Z = z] = \mu + \rho_{XZ}\, \sigma_X/\sigma_Z\, (z - 2\mu) = \mu + \rho_{XY}\, \sigma_X/2\sigma_Y\, (2y - 2\mu) = \mu + \rho_{XY}\, \sigma_X/\sigma_Y\, (y - \mu)$$

$$\mathrm{Var}(X \mid Z = z) = \sigma_X{}^2(1 - \rho_{XZ}{}^2) = \sigma_X{}^2(1 - \rho_{XY}{}^2)$$

where ρ_{XZ} is the correlation between X and Z. The previous line follows because of the following:

$$\rho_{XZ} = \mathrm{Cov}(X,Z)/\sigma_X\sigma_Z = 2\mathrm{Cov}(X,Y)/2\sigma_X\sigma_Y = \mathrm{Cov}(X,Y)/\sigma_X\sigma_Y = \rho_{XY}$$

As can be seen above, the conditional expected value and the conditional variance of X are the same for an investor who learns the value of Y and an investor who learns the value of Z. That is,

$$\mathrm{E}[X \mid Y = y] = \mathrm{E}[X \mid Z = z]$$

$$\mathrm{Var}(X \mid Y = y) = \mathrm{Var}(X \mid Z = z)$$

If the investor of X has mean-variance utility, the investor equally prefers learning about Y and learning about Z.

Thus far, this model illustrates that the investor of X has the same preference over the signals Y and Z. However, the next part of this model illustrates that when comparing regressions of X on Y and X on Z, Z has a smaller coefficient than Y. In contrast, when R-squared is used as the metric, a regression of X on Y and a regression of X on Z have the same R-squared. In this model, the R-squared is invariant to scale transformations of variables, whereas the coefficient is sensitive to such transformations.

A regression of X on Y would give a coefficient on Y of $\rho_{XY}\, \sigma_X/\sigma_Y$ because it measures how $\mathrm{E}[X \mid Y = y]$ varies with y. This is interpreted as the coefficient on Y:

$$\mathrm{Coef}_X(Y) = \rho_{XY}\, \sigma_X/\sigma_Y$$

The R-squared of a regression of X on Y is calculated as $1 - (\mathrm{Var}(X \mid Y = y)/\mathrm{Var}(X)) = 1 - \sigma_X{}^2(1 - \rho_{XY}{}^2)/\sigma_X{}^2 = \rho_{XY}{}^2$:

$$\mathrm{R}^2{}_X(Y) = \rho_{XY}{}^2$$

Similarly, a regression of X on Z would give a coefficient on Z of

$$\mathrm{Coef}_X(\mathrm{Z}) = \rho_{XY}\, \sigma_X/2\sigma_Y$$

Note that this is half of the coefficient on Y:

$$½ \times \mathrm{Coef}_X(Y) = \mathrm{Coef}_X(Z)$$

The R-squared of a regression of X on Z is calculated as $\rho_{XY}{}^2$:

$$R^2{}_X(Z) = \rho_{XY}{}^2$$

Note that the R-squared of regressing X on Y and the R-squared of regressing X on Z are the same:

$$R^2{}_X(Y) = R^2{}_X(Z)$$

In summary, although Y and Z have the same value to an investor of X, Z has a smaller coefficient than Y but the same R-squared as Y. Thus, under a mean-variance framework, the R-squared maps more closely to informativeness than the coefficient.

2.2. Simulation

Based on the above conceptual difference, this paper provides a simulation in which coefficients and R-squareds can provide different or opposite inferences regarding the informativeness of earnings. The simulation can help to confirm the results of the theoretical model in the previous section. To generate values for the simulation, this paper follows the above example and generates $u \sim N(\mu, \sigma^2)$, $e \sim N(0, \sigma^2)$, and $d \sim N(0, \sigma^2)$, and u, e, and d are independent. Then, this implies the following:

$$\sigma_X{}^2 = \mathrm{Var}(u + e) = \mathrm{Var}(u) + \mathrm{Var}(e) = \sigma^2 + \sigma^2 = 2\sigma^2$$

$$\sigma_Y{}^2 = \mathrm{Var}(u + e) = \mathrm{Var}(u) + \mathrm{Var}(d) = \sigma^2 + \sigma^2 = 2\sigma^2$$

$$\sigma_Z{}^2 = 4\sigma_Y{}^2 = 8\sigma^2$$

In addition,

$$\mathrm{Cov}(X,Y) = \mathrm{Cov}(u + e, u + d) = \mathrm{Cov}(u, u) = \mathrm{Var}(u) = \sigma^2$$

$$\rho_{XY} = \mathrm{Cov}(X,Y)/\sigma_X\sigma_Y = 1/2$$

$$\mathrm{Var}(X \mid Y = y) = \sigma_X{}^2(1 - \rho_{XY}{}^2) = 4\sigma^2$$

$$\mathrm{Cov}(X,Z) = \mathrm{Cov}(X,2Y) = \mathrm{Cov}(u + e, 2u + 2d) = \mathrm{Cov}(u, 2u) = 2 \times \mathrm{Cov}(u, u) = 2 \times \mathrm{Var}(u) = 2\sigma^2$$

$$\rho_{XZ} = \mathrm{Cov}(X,Z)/\sigma_X\sigma_Z = 2\sigma^2/\mathrm{sqrt}(2\sigma^2 \times 8\sigma^2) = 1/2$$

$$\mathrm{Var}(X \mid Z = z) = \sigma_X{}^2(1 - \rho_{XY}{}^2) = 4\sigma^2$$

To generate values for the simulation, assume $\mu = \sigma^2 = 1$.
This setup implies that $\sigma_X{}^2 = 2$, $\sigma_Y{}^2 = 2$, $\sigma_Z{}^2 = 8$, $\rho_{XY} = 1/2$. In addition,

$$\mathrm{Coef}_X(Y) = \rho_{XY}\ \sigma_X/\sigma_Y = 1/2$$

$$R^2{}_X(Y) = \rho_{XY}{}^2 = 1/4$$

$$\mathrm{Coef}_X(Z) = \rho_{XZ}\ \sigma_X/\sigma_Z = 1/2 \text{ x } \mathrm{sqrt}(2\sigma^2)/\mathrm{sqrt}(8\sigma^2) = 1/4$$

$$R^2{}_X(Z) = \rho_{XZ}{}^2 = 1/4$$

This numerical example is consistent with the conceptual difference described in Section 2.1, in which Y and Z provide the same information, but Z has a smaller coefficient and the same R-squared as Y. In fact, it is possible to have a situation in which the coefficient and the R-squared draw opposite conclusions. For example, consider a signal Z^* which is on a smaller scale than Y and has a slightly larger variance. The smaller scale will translate to a larger coefficient than Y, whereas the larger variance will translate to a smaller R-squared than Y.

$$Z^* = 0.5 \times Y + h = 0.5 \times u + 0.5 \times d + h$$

where $h \sim N(0, 0.25)$.

The coefficient and R-squared for Z^* are given by the following:

$$\sigma_{Z^*}{}^2 = \mathrm{Var}(0.5 \times u + 0.5 \times d + h) = 0.25 + 0.25 + 0.25 = 0.75$$

$$\mathrm{Cov}(X,Z^*) = \mathrm{Cov}(u + e, 0.5\, u + 0.5\, d + h) = 0.5\, \mathrm{Cov}(u, u) = 0.5\, \mathrm{Var}(u) = 0.5$$

$$\rho_{XZ^*} = \mathrm{Cov}(X,Z^*)/\sigma_X\sigma_{Z^*} = 0.5/\mathrm{sqrt}(2 \times 0.75) = 0.5/\mathrm{sqrt}\,(1.5)$$

$$\mathrm{Coef}_X(Z^*) = \rho_{XZ^*}\, \sigma_X/\sigma_{Z^*} = 0.5/\mathrm{sqrt}\,(1.5) \times \mathrm{sqrt}(2)/\mathrm{sqrt}(0.75) = 0.5 \times \mathrm{sqrt}(16/9) = 2/3$$

$$\mathrm{R}^2{}_X(Z^*) = \rho_{XZ}{}^2 = 0.25/1.5 = 1/6$$

The above shows that $\mathrm{Coef}_X(Z^*) > \mathrm{Coef}_X(Y)$, but $\mathrm{R}^2{}_X(Z^*) < \mathrm{R}^2{}_X(Y)$. Thus, this is a case in which the coefficient and the R-squared can provide opposite inferences. An example of this could be two industries that differ in terms of earnings multiples and earnings smoothness. An industry with high average earnings multiples could have a higher coefficient than an industry with low multiples. However, if the same industry with high average earnings multiples has low earnings smoothness, it could have lower R-squareds than an industry with high earnings smoothness.

To generate data for the simulation, this paper generates all random variables (i.e., u, e, d, and h) using a sample size of 10,000 and computes X, Y, Z, and Z^*. Table 1 presents the results of the simulation for regressions of X on Y (Panel A), X on Z (Panel B), and X on Z^* (Panel C). As expected, the regression coefficients are highly similar to the theoretical coefficients. A comparison of Panels A and B reveals that as predicted, the coefficient on Y (0.50 theoretical, 0.51 estimated) is larger than the coefficient on Z (0.25 theoretical, 0.25 estimated). However, both Y and Z have the same R-squareds (0.25 theoretical, 0.26 estimated). A comparison of Panels A and C reveals that also as predicted, the coefficient on Y is smaller than the coefficient on Z^*, but the R-squared of Y is larger than the R-squared of Z^*. Thus, it is possible for the coefficient and the R-squared to draw opposite conclusions. As in the small theoretical model in Section 2.1, under a mean-variance framework, the R-squared more closely matches informativeness than the coefficient.

Table 1. Simulation comparison of coefficients and R-squareds. This table presents simulation results of regressing X, a normally distributed random variable that represents future value, on normally distributed signals Y, Z, and Z^*. Y is a signal that contains information about X. Z is also a signal that contains information about X and has a realization that is exactly two times the realization of Y. Z^* is half the realization of Y plus normally distributed random noise.

	Predicted	**Estimate**	**(t-Stat)**
	Panel A: Regression of X on Y		
Intercept	0.00	−0.01	(−0.92)
Y	0.50	0.51	(58.96)
R2	0.25	0.26	
N		10,000	
	Panel B: Regression of X on Z		
Intercept	0.00	−0.01	(−0.92)
Z	0.25	0.25	(58.96)
R2	0.25	0.26	
N		10,000	
	Panel C: Regression of X on Z^*		
Intercept	0.00	−0.01	(−0.71)
Z^*	0.67	0.68	(45.47)
R2	0.17	0.17	
N		10,000	

2.3. Coefficients and R-Squareds in Archival Research

Despite the conceptual difference described in the previous subsections, many papers focus on coefficients and not R-squareds.[2] To examine the prevalence of the use of coefficients and R-squareds in the literature, this paper reviews papers published from 1990–2023 in *Journal of Accounting and Economics*, *Journal of Accounting Research*, and *The Accounting Review*.[3] The search criteria are all papers with at least one of the following keywords: ERC, ERCs, earnings response coefficient, and earnings response coefficients. The paper must also be an archival paper and have at least one regression of returns on earnings surprises. This resulted in a total of 34 papers reviewed. Appendix A lists the papers reviewed. Of the papers reviewed, all papers use coefficients to examine the informativeness of earnings, and nine papers (26%) use R-squareds to examine the informativeness of earnings. Perhaps interestingly, of the more recent papers published from 2000–2023 (19 papers), only 3 papers (16%) use R-squareds to examine the informativeness of earnings. This review suggests that the recent literature on ERCs has focused substantially more on coefficients than R-squareds. Thus, it is important to next document the extent to which coefficients and R-squareds can draw opposite inferences in archival data.

3. Empirical Research Design

This paper assesses the extent to which coefficients and R-squareds draw opposite inferences regarding the informativeness of earnings and related performance measures in archival data. This is important because although coefficients and R-squareds can draw opposite inferences theoretically, the extent to which this occurs in archival data is largely unknown. Although the coefficient measure is common and standardized in the literature, this is not the case for R-squareds. Thus, this paper examines four different measures of R-squareds: R-squared, adjusted R-squared, incremental R-squared, and incremental adjusted R-squared. Each of these measures has potential theoretical appeal. R-squared captures the proportion of variation in the dependent variable that is explained by the independent variables. Adjusted R-squared adjusts the R-squared value to penalize the inclusion of irrelevant independent variables. Incremental (adjusted) R-squared, which is calculated as the difference between the (adjusted) R-squared of a regression with the independent variable of interest and the (adjusted) R-squared of a regression without the independent variable of interest, captures the proportion of variation in the dependent variable explained by the independent variable of interest that is incremental to other independent variables in the regression (adjusted for the adjusted R-squared penalties).[4] In total, this paper examines five different measures of informativeness.

To assess the extent to which coefficients and R-squareds draw opposite inferences, this paper estimates the following equation by Fama–French 48 industries:

$$CAR[-1,+1] = \beta_0 + \beta_1 EARN\_SURP + \gamma Controls + \varepsilon \quad (1)$$

Variables are defined in Appendix B. $CAR[-1,+1]$ is the announcement period return, *EARN_SURP* is the earnings surprise, γ is a vector of coefficients on controls, and *Controls* is a vector of control variables.[5] This paper estimates Equation (1) both without and with control variables. When estimating control variables, this paper includes control variables that are common in ERC regressions in prior literature (e.g., Teoh and Wong 1993; Lobo et al. 2017). Control variables include return on assets (*ROA*), size (*SIZE*), book to market (*BM*), revenues (*REV*), cash flows from operations (*CFO*), asset growth (*AG*), revenue surprise (*REV_SURP*), cash flows from operations surprise (*CFO_SURP*), and year fixed effects.

This paper estimates Equation (1) separately by Fama–French 48 industries to draw comparisons between industries. This corresponds to the empirical question of whether earnings are more informative in certain industries than in other industries. For example, consider two hypothetical industries, Industry A and Industry B. If the coefficient on earnings in Industry A is larger (smaller) than the coefficient on earnings in Industry B, then the coefficient test would conclude that earnings are more (less) informative for

Industry A firms than Industry B firms. Similarly, if the R-squared of the regression in Industry A is larger (smaller) than the R-squared of the regression in Industry B, then the R-squared test would conclude that earnings are more (less) informative for Industry A firms than Industry B firms.

For each Fama–French 48 industry pair (48 choose 2 = 1128 possible pairs), this paper computes a measure, *Disagree*, an indicator variable that takes a value of 1 if two measures (e.g., coefficients and R-squareds) draw opposite inferences and a value of 0 if the two measures draw the same inference. Using the same example, if both the coefficient and the R-squared in the regression for Industry A are greater than their respective counterparts for Industry B, then the coefficient and R-squared draw the same inference. In other words, they both suggest that earnings are more informative for Industry A firms than Industry B firms. In this case, *Disagree* would take a value of 0. However, if hypothetically, the coefficient for Industry A firms is greater than the coefficient for Industry B firms, but the R-squared for Industry A firms is less than the R-squared for Industry B firms, then the coefficient and R-squared do not agree because they draw opposite inferences about the informativeness of earnings. The coefficient value would suggest that earnings are more informative for Industry A firms, whereas the R-squared value would suggest earnings are more informative for Industry B firms. In this case, *Disagree* would take a value of 1 for the two industries being compared, Industry A and Industry B.

Then, this paper computes *Disagreement* as the average percentage of the time that two measures being compared draw opposite inferences about two different Fama–French 48 industries (i.e., the average value of *Disagree* across all 1128 possible industry pairs). Intuitively, *Disagreement* measures the extent to which two measures (e.g., coefficients and R-squareds) draw opposite inferences about the informativeness of earnings in archival data.

In addition to examining earnings as a performance measure, this paper also examines two other performance measures, revenue surprise (*REV_SURP*) and cash flows from operations surprises (*CFO_SURP*). This is important given the increasing focus on performance measures that are alternatives to earnings (e.g., Sloan 1996; Jegadeesh and Livnat 2006). For regressions with no controls, *EARN_SURP* in Equation (1) is replaced with either *REV_SURP* for revenue surprises or *CFO_SURP* for cash flows from operations surprises. For regressions with controls, this paper examines the same Equation (1), but rather than examining the coefficient, R-squared, adjusted R-squared, incremental R-squared, and incremental adjusted R-squared values for *EARN_SURP*, the metrics for *REV_SURP* and *CFO_SURP* are examined.[6]

4. Data

The sample in this paper contains 97,472 observations in the intersection of Compustat and CRSP from 1989–2021. This paper requires all main and control variables so that the number of observations is the same for all analyses. Thus, the sample begins in 1989 because it is the first full year in which the statement of cash flows is a required disclosure. The sample ends in 2021 because data were collected in 2023, and thus 2021 is the latest full year of available data. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the impact of outliers on estimation results.

Table 2 presents descriptive statistics and Table 3 presents correlations. Mean *ROA* is −0.01, consistent with the proliferation of loss firms in recent years. *CAR*[−1,+1] and *EARN_SURP* are positively correlated (Pearson corr. 0.07, Spearman corr. 0.09). Similarly, *CAR*[−1,+1] has positive correlations with both *REV_SURP* and *CFO_SURP*. Also, *EARN_SURP*, *REV_SURP*, and *CFO_SURP* are all pairwise positively correlated, consistent with correlation in fundamentals.

Table 2. Descriptive statistics. This table presents descriptive statistics for the 97,472 observations in the sample from 1989–2021. Variables are defined in Appendix B.

Variable	Mean	SD	p25	p50	p75
CAR[−1,+1]	0.00	0.09	−0.04	0.00	0.04
EARN_SURP	−0.02	0.25	−0.03	0.00	0.03
REV_SURP	0.04	0.48	−0.01	0.04	0.14
CFO_SURP	0.00	0.20	−0.03	0.01	0.04
ROA	−0.01	0.20	−0.01	0.03	0.08
SIZE	3222	9970	73	335	1599
BM	0.63	0.59	0.27	0.50	0.83
REV	1.10	0.91	0.43	0.93	1.51
CFO	0.05	0.17	0.01	0.07	0.14
AG	0.14	0.39	−0.02	0.06	0.19

Table 3. Correlations. This table presents correlations for the 97,472 observations in the sample from 1989–2021. Pearson (Spearman) correlations are above (below) the main diagonal. Variables are defined in Appendix B.

Variable	*CAR*[−1,+1]	*EARN_SURP*	*REV_SURP*	*CFO_SURP*	*ROA*	*SIZE*	*BM*	*REV*	*CFO*	*AG*
CAR[−1,+1]		0.07	0.03	0.03	0.06	−0.01	0.03	0.03	0.05	0.00
EARN_SURP	0.09		0.16	0.21	0.22	0.02	−0.13	0.05	0.07	0.07
REV_SURP	0.06	0.26		0.12	0.12	0.00	−0.12	0.24	0.05	0.24
CFO_SURP	0.05	0.26	0.16		0.07	0.01	−0.03	0.02	0.21	0.01
ROA	0.07	0.35	0.27	0.14		0.13	0.02	0.27	0.79	−0.01
SIZE	0.02	0.04	−0.01	0.02	0.31		−0.15	−0.08	0.13	0.00
BM	0.02	−0.07	−0.02	−0.02	−0.20	−0.38		−0.08	−0.02	−0.15
REV	0.03	0.10	0.36	0.06	0.41	−0.12	−0.11		0.25	0.18
CFO	0.06	0.16	0.13	0.38	0.67	0.31	−0.20	0.37		−0.03
AG	0.03	0.15	0.41	0.05	0.39	0.18	−0.21	0.19	0.21	

5. Results

Table 4 presents the five measures that correspond to estimating Equation (1) for the full sample and by each Fama–French 48 industry. Table values are multiplied by 100 for presentation purposes. When examining coefficients, the findings corroborate several prior findings. For the full sample ("All" row), the coefficient is 2.6 (0.026 when unscaled), which is similar to the coefficient reported in Table 1 by Lipe et al. (1998). The R-squared value is 0.6%, which is lower than the 0.8% reported by Lipe et al. (1998).[7] The lower R-squared value could be attributable to this paper using a more recent sample period that ends in 2021 compared to a sample that ends in 1995 in Lipe et al. (1998) because of the well-documented decline in the relevance of earnings over time (e.g., Lev 1989; Collins et al. 1997; Brown et al. 1999; Core et al. 2003; and Lev and Gu 2016).

Table 5 documents *Disagreement*, the percentage of time that two measures being compared draw opposite conclusions when comparing two different subsamples. Panel A examines *Disagreement* for earnings surprises and reveals that coefficients and R-squared values disagree 14.9 percent of the time. *Disagreement* is slightly greater between coefficients and adjusted R-squareds, as they disagree 15.3 percent of the time. Incremental R-squared and incremental adjusted R-squared are the same as R-squared and incremental R-squared because there are no control variables, so they have the same respective *Disagreement* with coefficients. The findings suggest that it is possible for coefficients and R-squareds to draw opposite inferences about the informativeness of earnings approximately 15 percent of the time.

Table 4. ERC regressions by Fama–French 48 industries with no controls. This table presents regression results for the following equation for each Fama–French 48 industry and for all firms: $CAR[-1,+1] = \beta_0 + \beta_1 EARN\_SURP + \varepsilon$. $CAR[-1,+1]$ is market-adjusted return during the earnings announcement period. *EARN_SURP* is earnings surprise. Variables are defined in Appendix B. All table values are multiplied by 100 for presentation purposes. *Coef* is the coefficient of earnings surprise. *R2* is the R-squared of the regression, *AdjR2* is the adjusted R-squared of the regression, *IncrR2* is the incremental R-squared of *EARN_SURP*, and *IncrAdjR2* is the incremental adjusted R-squared of *EARN_SURP*.

IND	Name	Coef	R2	AdjR2	IncrR2	IncrAdjR2
1	Agric	−1.4	0.2	−0.2	0.2	−0.2
2	Food	1.5	0.1	0.0	0.1	0.0
3	Soda	4.3	1.3	1.0	1.3	1.0
4	Beer	−0.1	0.0	−0.3	0.0	−0.3
5	Smoke	6.8	2.1	1.3	2.1	1.3
6	Toys	4.1	1.5	1.4	1.5	1.4
7	Fun	2.6	0.6	0.6	0.6	0.6
8	Books	4.4	2.4	2.3	2.4	2.3
9	Hshld	0.7	0.0	0.0	0.0	0.0
10	Clths	3.4	0.8	0.8	0.8	0.8
11	Hlth	3.2	0.9	0.9	0.9	0.9
12	MedEq	4.4	0.8	0.7	0.8	0.7
13	Drugs	2.6	0.4	0.3	0.4	0.3
14	Chems	2.6	0.4	0.3	0.4	0.3
15	Rubbr	0.4	0.0	−0.1	0.0	−0.1
16	Txtls	3.6	1.8	1.6	1.8	1.6
17	BldMt	4.7	2.0	2.0	2.0	2.0
18	Cnstr	1.4	0.2	0.1	0.2	0.1
19	Steel	4.6	2.4	2.3	2.4	2.3
20	FabPr	6.6	3.9	3.6	3.9	3.6
21	Mach	3.3	0.8	0.8	0.8	0.8
22	ElcEq	4.6	1.3	1.2	1.3	1.2
23	Autos	2.4	0.6	0.6	0.6	0.6
24	Aero	4.2	0.9	0.7	0.9	0.7
25	Ships	2.6	0.9	0.4	0.9	0.4
26	Guns	−9.5	4.7	4.2	4.7	4.2
27	Gold	4.5	2.2	1.9	2.2	1.9
28	Mines	1.6	0.3	0.1	0.3	0.1
29	Coal	6.1	7.1	6.4	7.1	6.4
30	Oil	1.3	0.2	0.2	0.2	0.2
31	Util	3.4	1.5	1.4	1.5	1.4
32	Telcm	1.9	0.6	0.6	0.6	0.6
33	PerSv	2.1	0.4	0.3	0.4	0.3
34	BusSv	2.5	0.4	0.4	0.4	0.4
35	Comps	0.8	0.0	0.0	0.0	0.0
36	Chips	0.9	0.0	0.0	0.0	0.0
37	LabEq	3.1	0.5	0.4	0.5	0.4
38	Paper	1.4	0.2	0.1	0.2	0.1
39	Boxes	−0.9	0.0	−0.3	0.0	−0.3
40	Trans	2.3	0.7	0.6	0.7	0.6
41	Whlsl	4.8	1.7	1.6	1.7	1.6
42	Rtail	2.6	0.6	0.6	0.6	0.6
43	Meals	2.4	0.6	0.6	0.6	0.6
44	Banks	3.7	2.3	2.3	2.3	2.3
45	Insur	2.3	0.5	0.5	0.5	0.5
46	RlEst	1.8	0.6	0.5	0.6	0.5
47	Fin	2.9	0.9	0.9	0.9	0.9
48	Other	3.1	0.8	0.5	0.8	0.5
All		2.6	0.6	0.6	0.6	0.6

Table 5. Disagreement of coefficients and R-squareds with no controls. This table presents the extent to which coefficients and several measures of R-squareds draw opposite inferences regarding the informativeness of earnings and other performance measures. Table values represent *Disagreement*, the average percentage of the time that two measures being compared draw opposite inferences about the informativeness of earnings surprise, revenue surprise, or cash flows from operations surprise for two different Fama–French 48 industries in regressions with no control variables. *EARN_SURP* is earnings surprise. *REV_SURP* is revenue surprise. *CFO_SURP* is cash flows from operations surprise. Variables are defined in Appendix B. *Coef* is the coefficient on the variable of interest. *R2* is the R-squared of the regression, *AdjR2* is the adjusted R-squared of the regression, *IncrR2* is the incremental R-squared of the variable of interest, and *IncrAdjR2* is the incremental adjusted R-squared of the variable of interest.

	R2	***AdjR2***	***IncrR2***	***IncrAdjR2***
		Panel A: *EARN_SURP*		
Coef	14.9	15.3	14.9	15.3
R2		5.5	0.0	5.5
AdjR2			5.5	0.0
IncrR2				5.5
		Panel B: *REV_SURP*		
Coef	16.6	14.9	16.6	14.9
R2		11.4	0.0	11.4
AdjR2			11.4	0.0
IncrR2				11.4
		Panel C: *CFO_SURP*		
Coef	19.8	20.2	19.8	20.2
R2		19.1	0.0	19.1
AdjR2			19.1	0.0
IncrR2				19.1

The consistent level of discrepancies between coefficients and R-squareds documented in Table 5 and the low level of R-squareds documented in Table 4 is part of a longstanding puzzle of the inability of fundamental information to explain returns, even ex-post (Roll 1988). These findings suggest that not all influential variables are captured by the standard ERC model. Future research could explore additional variables or statistical techniques to account for these inconsistencies.

Panels B and C reveal similar levels of *Disagreement* between coefficients and R-squareds for revenue surprises and cash flows from operations surprises. *Disagreement* between coefficients and the four R-squared measures ranges from 14.9–16.6 percent for revenue surprises and 19.8–20.2 percent for cash flows from operations surprises. Overall, the findings from Table 5 suggest that there is a non-trivial number of instances in which coefficients and R-squareds draw opposite inferences regarding the informativeness of earnings and other performance measures.[8]

Table 6 presents coefficients and R-squared values when Equation (1) is estimated with controls. Perhaps unsurprisingly, average R-squared values across industries are larger in Table 6 than in Table 4 (8.9 vs. 1.1, untabulated), which reflects the additional explanatory power from including control variables. However, average incremental R-squared values are smaller in Table 6 than in Table 4 (0.8 vs. 1.1, untabulated), which reflects the fact that earnings surprises contain less incremental information after considering the information in control variables.

Table 6. ERC regressions by Fama–French 48 industries with controls. This table presents regression results for the following equation for each Fama–French 48 industry: $CAR[-1,+1] = \beta_0 + \beta_1 EARN\_SURP + \gamma Controls + \varepsilon$. $CAR[-1,+1]$ is market-adjusted return during around earnings announcement period. *EARN_SURP* is earnings surprise. Controls include return on assets (*ROA*), size (*SIZE*), book to market (*BM*), revenues (*REV*), cash flows from operations (*CFO*), asset growth (*AG*), revenue surprise (*REV_SURP*), cash flows from operations surprise (*CFO_SURP*), and year fixed effects. Variables are defined in Appendix B. All table values are multiplied by 100 for presentation purposes. *Coef* is the coefficient of earnings surprise. *R2* is the R-squared of the regression, *AdjR2* is the adjusted R-squared of the regression, *IncrR2* is the incremental R-squared of *EARN_SURP*, and *IncrAdjR2* is the incremental adjusted R-squared of *EARN_SURP*.

IND	Name	Coef	R2	AdjR2	IncrR2	IncrAdjR2
1	Agric	−2.3	20.7	5.9	0.4	0.1
2	Food	1.3	3.8	1.0	0.1	0.0
3	Soda	4.2	18.2	6.7	1.0	0.8
4	Beer	1.7	17.1	3.6	0.1	−0.3
5	Smoke	7.1	34.4	3.1	1.2	0.7
6	Toys	5.0	9.9	4.6	1.7	1.7
7	Fun	3.4	6.2	3.0	0.9	0.8
8	Books	4.3	9.3	4.7	1.5	1.5
9	Hshld	−0.6	3.8	1.3	0.0	0.0
10	Clths	2.5	5.5	1.7	0.3	0.3
11	Hlth	3.8	3.5	1.4	1.1	1.1
12	MedEq	4.1	3.5	2.2	0.6	0.5
13	Drugs	2.1	1.8	0.9	0.2	0.2
14	Chems	1.7	3.7	1.5	0.1	0.1
15	Rubbr	1.6	9.0	3.7	0.2	0.1
16	Txtls	4.0	10.3	1.4	1.4	1.3
17	BldMt	3.9	5.4	3.2	1.0	1.0
18	Cnstr	2.3	6.3	2.7	0.4	0.4
19	Steel	5.4	6.7	3.8	2.1	2.1
20	FabPr	7.9	9.9	−2.3	3.2	3.3
21	Mach	3.2	2.8	1.6	0.6	0.5
22	ElcEq	5.9	5.3	3.4	1.5	1.5
23	Autos	2.6	3.9	1.1	0.5	0.5
24	Aero	5.5	11.3	3.7	1.3	1.2
25	Ships	3.3	23.7	5.1	0.7	0.4
26	Guns	−16.2	26.3	4.6	8.7	10.5
27	Gold	4.1	15.9	0.6	1.1	0.9
28	Mines	0.7	13.9	4.5	0.0	−0.2
29	Coal	0.6	39.9	9.4	0.0	−1.1
30	Oil	0.8	1.4	0.9	0.0	0.0
31	Util	3.6	4.3	2.9	1.2	1.2
32	Telcm	1.2	3.7	1.9	0.2	0.1
33	PerSv	1.9	4.8	0.9	0.2	0.1
34	BusSv	2.7	1.6	1.2	0.4	0.3
35	Comps	0.3	2.1	0.7	0.0	0.0
36	Chips	0.2	1.3	0.5	0.0	0.0
37	LabEq	2.7	2.3	0.2	0.2	0.2
38	Paper	0.8	3.7	−0.4	0.0	−0.1
39	Boxes	1.1	31.0	20.1	0.0	−0.3
40	Trans	1.9	2.9	0.9	0.3	0.3
41	Whlsl	5.0	3.2	2.1	1.5	1.5
42	Rtail	3.1	2.5	1.7	0.7	0.7
43	Meals	2.5	2.7	0.8	0.5	0.4
44	Banks	3.5	5.7	5.2	1.6	1.6
45	Insur	2.0	2.5	1.2	0.3	0.3
46	RlEst	1.0	5.0	−0.9	0.2	0.0
47	Fin	2.6	2.5	1.2	0.6	0.6
48	Other	2.1	12.9	3.6	0.3	0.1

In untabulated analyses, the coefficients and R-squared values for Equation (1) estimated with controls are compared for *EARN_SURP*, *ROA*, *SIZE*, *BM*, *REV*, *CFO*, *AG*, *REV_SURP*, and *CFO_SURP*. As expected, *EARN_SURP* has the highest average incremental R-squared (0.8), as earnings surprises have traditionally been the focus during earnings announcement periods. Perhaps surprisingly, *BM* has the second highest incremental R-squared (0.5), which reflects the strength of the value premium (e.g., Fama and French 1993). *REV_SURP*, *ROA*, and *AG* are the next highest in terms of incremental R-squareds (0.3 for all three variables). This reflects the focus on revenue surprises during earnings announcements, the profitability premium, and the asset growth premium (e.g., Fama and French 2015). Within particular industries, *EARN_SURP* and *CFO_SURP* appear to at least partially be substitutes. The correlation between the incremental R-squareds for *EARN_SURP* and *CFO_SURP* across the Fama–French 48 industries is −0.07. This is consistent with market participants reacting more strongly to cash flow surprises in industries in which they react less to earnings surprises. Perhaps interestingly, the correlation between the incremental R-squareds for *EARN_SURP* and each of *ROA*, *SIZE*, and *BM* are positive. This suggests that earnings surprises are more informative in industries in which the profitability, size, and value factors have greater associations with returns.

Table 7 documents *Disagreement* corresponding to estimating Equation (1) with controls. Panel A reveals that *Disagreement* between coefficients and R-squareds ranges from 13.3–42.6 percent for earnings surprises. Panels B and C reveal that disagreement between coefficients and R-squareds can be even greater for revenue surprises and cash flows from operations surprises, ranging from 22.0–48.8 percent and 46.8–56.7 percent, respectively. Overall, Table 7 suggests that in some cases, there can be a substantial number of instances in which coefficients and R-squareds draw opposite inferences about the informativeness of earnings and other performance measures.

Table 7. Disagreement of coefficients and R-squareds with control variables. This table presents the extent to which coefficients and several measures of R-squareds draw opposite inferences regarding the informativeness of earnings and other performance measures when control variables are included. Table values represent *Disagreement*, the average percentage of the time that two measures being compared draw opposite inferences about the informativeness of earnings surprise, revenue surprise, or cash flows from operations surprise for two different Fama–French 48 industries in regressions with control variables. *EARN_SURP* is earnings surprise. *REV_SURP* is revenue surprise. *CFO_SURP* is cash flows from operations surprise. Variables are defined in Appendix B. *Coef* is the coefficient on the variable of interest. *R2* is the R-squared of the regression, *AdjR2* is the adjusted R-squared of the regression, *IncrR2* is the incremental R-squared of the variable of interest, and *IncrAdjR2* is the incremental adjusted R-squared of the variable of interest.

	R2	***AdjR2***	***IncrR2***	***IncrAdjR2***
		Panel A: *EARN_SURP*		
Coef	42.6	42.3	13.3	15.7
R2		23.8	38.4	43.5
AdjR2			36.4	39.5
IncrR2				5.5
		Panel B: *REV_SURP*		
Coef	43.4	48.8	22.0	31.1
R2		23.8	30.3	47.5
AdjR2			39.2	42.6
IncrR2				19.5
		Panel C: *CFO_SURP*		
Coef	51.8	56.7	46.8	47.9
R2		23.8	33.7	52.1
AdjR2			32.7	41.6
IncrR2				20.2

6. Bootstrapped Standard Errors

This section proposes a bootstrapping approach to estimate two-way cluster robust standard errors for R-squareds. Although this paper proposes a greater focus on examining R-squareds as a measure of the informativeness of earnings, the calculation of standard errors for R-squareds is far less common in the literature than such calculation for coefficients. The calculation of standard errors, particularly two-way cluster robust standard errors, could help researchers draw statistical inferences using R-squared values.

The bootstrapping approach proposed in this paper is based approach of Ohtani (2000), Cameron et al. (2008), Gow et al. (2010), and Cameron et al. (2011). Ohtani (2000) develops a bootstrapping approach to estimate standard errors for R-squareds. Cameron et al. (2008) developed a bootstrapping approach to estimate clustered standard errors. Cameron et al. (2011) and Gow et al. (2010) develop and apply an approach for multi-way clustering of standard errors. This paper follows these approaches to estimate standard errors for R-squareds.

The approach begins with nonoverlapping block bootstrapping by firm and by year to simulate one-way clustering. For a bootstrapped sample by firm (year), this paper samples firms (years) from the data, with replacement, until the same number of firms (years) as the number of firms (years) in the data is sampled. This paper then includes all firm–years that correspond to the sampled firms (years) as the bootstrapped sample by firm (year). Bootstrapping is performed 100 times by firm and another 100 times by year. This results in 100 R-squared values for bootstrapped samples by firm and 100 R-squared values for bootstrapped samples by year. This paper further computes 100 R-squared values for 100 bootstrapped samples by firm–year, in which this paper randomly selects firm–years with replacement from the data set until the same number of firm–years as the number of firm–years in the data is sampled. This paper then computes $v = v_i + v_t - v_{it}$, where v_i is the variance of the R-squared values for the bootstrapped samples by firm, v_t is the variance of the R-squared values for the bootstrapped samples by year, and v_{it} is the variance of the R-squared values for the bootstrapped samples by firm–year. The standard error is the square root of the bootstrapped variance estimate v.

To assess the validity of this method, this paper first uses this approach to estimate the standard error of coefficients rather than R-squareds. This paper compares the bootstrapped standard errors to analytically estimated standard errors based on the approach of Gow et al. (2010). As a benchmark, this paper computes analytical standard errors using both two-way clustering and no clustering. If bootstrapped standard errors are accurate, they should resemble two-way clustered analytical standard errors more than non-clustered analytical standard errors. After assessing the validity of this method for coefficients, this paper then uses this approach to estimate bootstrapped standard errors for R-squared values.

Table 8 presents standard error estimates for coefficients and R-squareds for Equation (1) estimated with no controls for each Fama–French 48 industry. For coefficients, no clustering analytical standard errors, two-way cluster-robust analytical standard errors, and two-way cluster-robust bootstrapped standard errors are presented. As expected, the mean standard error across industries is larger for two-way cluster-robust approaches than for no clustering because it is reasonable to expect correlation in error terms both across firms and over time. Furthermore, two-way cluster-robust analytical standard errors and two-way cluster-robust bootstrapped standard errors resemble each other more than they resemble standard errors with no clustering (mean standard errors of 1.7 and 1.8, compared to 1.2 for no clustering). There is also considerable variation across industries in the difference between no clustering standard errors and cluster-robust standard errors. Whereas these standard errors are similar in certain industries, cluster-robust standard error values are double the no clustering standard error values in other industries.

Table 8. Analytical and bootstrapped standard errors for ERC regressions. This table presents analytical and bootstrapped standard errors for ERC regressions with no controls for each Fama–French 48 industry. No cluster refers to analytically calculated standard errors with no clustering. Analytical refers to two-way cluster robust standard errors calculated analytically. Bootstrap refers to two-way cluster robust standard errors estimated using bootstrapping.

IND	Name	Coefficient			*R2*
		No Cluster	Analytical	Bootstrap	Bootstrap
1	Agric	1.8	2.2	1.7	0.7
2	Food	1.1	2.3	2.6	0.6
3	Soda	2.1	1.2	2.5	1.0
4	Beer	2.5	1.5	2.2	0.3
5	Smoke	4.1	6.0	8.2	5.9
6	Toys	1.2	1.4	1.3	0.9
7	Fun	0.9	1.4	1.5	0.7
8	Books	1.0	1.2	1.2	1.2
9	Hshld	0.8	1.4	1.5	0.4
10	Clths	1.1	1.9	2.0	1.2
11	Hlth	0.7	1.0	1.0	0.6
12	MedEq	0.9	0.9	0.9	0.3
13	Drugs	0.7	0.8	0.9	0.2
14	Chems	1.0	1.9	1.9	0.7
15	Rubbr	1.1	1.6	1.8	0.4
16	Txtls	1.2	1.6	1.7	1.7
17	BldMt	0.8	1.1	1.2	1.1
18	Cnstr	0.9	1.8	1.5	0.6
19	Steel	0.8	1.4	1.4	1.6
20	FabPr	1.8	2.1	2.5	2.9
21	Mach	0.6	1.4	1.4	0.7
22	ElcEq	0.9	1.2	1.2	0.7
23	Autos	0.8	1.2	1.2	0.5
24	Aero	1.9	3.6	4.0	1.7
25	Ships	1.9	2.5	2.9	2.2
26	Guns	3.2	4.4	4.6	5.1
27	Gold	1.8	2.7	4.0	3.6
28	Mines	1.4	2.5	2.1	1.1
29	Coal	2.0	2.3	3.3	5.8
30	Oil	0.4	0.5	0.5	0.1
31	Util	0.5	0.9	1.3	1.0
32	Telcm	0.5	0.8	0.9	0.5
33	PerSv	1.0	1.5	1.6	0.6
34	BusSv	0.4	0.6	0.6	0.2
35	Comps	0.7	0.9	1.0	0.2
36	Chips	0.6	0.9	1.0	0.1
37	LabEq	1.0	1.3	1.1	0.4
38	Paper	1.0	2.0	2.0	0.9
39	Boxes	2.4	2.4	2.7	0.9
40	Trans	0.6	0.7	1.1	0.6
41	Whlsl	0.6	0.7	0.5	0.4
42	Rtail	0.5	0.9	1.0	0.4
43	Meals	0.7	1.0	1.4	0.8
44	Banks	0.3	0.8	0.9	1.0
45	Insur	0.6	1.3	1.3	0.6
46	RlEst	0.9	1.7	1.2	0.6
47	Fin	0.5	1.4	1.3	0.9
48	Other	1.7	2.3	2.6	0.9
Mean		1.2	1.7	1.8	1.2

Table 9 presents Pearson and Spearman correlations for the three standard error measures for coefficients and also an *Agreement* measure, which is calculated as one minus

Disagreement. *Agreement* measures the proportion of time that two measures draw the same inferences about whether the standard error is larger in one Fama–French 48 industry than in another Fama–French 48 industry.

Table 9. Comparison of standard error estimation approaches. This table presents comparisons of standard error estimation approaches for coefficients on earnings surprises (*EARN_SURP*) for ERC regressions for each Fama–French 48 industry. Pearson is Pearson correlation. Spearman is Spearman correlation. Agreement is the average percentage of the time that two measures being compared draw the same inferences about whether the standard error is larger in one Fama–French 48 industry than in another Fama–French 48 industry. No clustering refers to analytically calculated standard errors with no clustering. Analytical refers to two-way cluster robust standard errors calculated analytically. Bootstrap refers to two-way cluster robust standard errors estimated using bootstrapping.

Clustering Methods	Pearson	Spearman	Agreement
Analytical and Bootstrap	95.7	93.0	90.8
Analytical and No clustering	90.2	87.3	85.6
Bootstrap and No clustering	87.5	84.9	84.7

Table 9 reveals that two-way cluster-robust analytical and two-way cluster-robust bootstrapped standard errors are highly correlated and have high *Agreement* (Pearson corr. = 95.7, Spearman corr. = 93.0, *Agreement* = 90.8). In contrast, both have lower correlation and lower *Agreement* with analytical standard errors with no clustering (Pearson corr., Spearman corr., and *Agreement* range from 84.7–90.2 percent). Thus, Tables 8 and 9 suggest that two-way cluster robust analytical and two-way cluster robust bootstrapped standard errors produce highly similar results. Table 8 then presents a two-way cluster of robust bootstrapped standard errors for R-squared values. Thus, this methodology permits the ability to draw statistical inferences for R-squared values that are robust to two-way clustering of error terms.

7. Conclusions

This paper examines coefficients and R-squareds as candidates for drawing inferences about the informativeness of earnings. Although both have been proposed as candidates, research has focused far more on coefficients than R-squareds. This paper first illustrates using a small theoretical model that under some circumstances, R-squareds map more closely to informativeness than coefficients. This paper then documents that coefficients and R-squareds can draw opposite inferences up to and around 50 percent of the time in certain archival settings. This paper then proposes a methodology to provide statistical inference by estimating two-way cluster robust standard errors for R-squareds. Overall, this paper suggests that future research can consider examining both coefficients and R-squareds as candidates for drawing inferences on the informativeness of earnings.

There may be several directions for future research. The model is limited by simplifying assumptions, such as the normality of variable distributions. These assumptions may not reflect the real complexity of financial markets or empirical data. Future research could explore different sets of assumptions or relax these assumptions. In addition, the model could be extended to take into account macroeconomic factors, such as inflation, GDP growth, or interest rates. These additional factors could improve the explanation of variation in returns. The advantages and shortcomings of coefficients and R-squareds can be explored in future research. For example, R-squared can be influenced by model complexity and coefficients can be affected by collinearity between variables.

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Appendix A. List of Earnings Response Coefficients Papers Reviewed

This appendix lists the papers reviewed to document the prevalence of the use of coefficients and R-squareds in the literature to draw inferences on the informativeness of earnings. The papers are published from 1990–2023, and the journals reviewed are *Journal of Accounting and Economics*, *Journal of Accounting Research*, and *The Accounting Review.* The search criteria are all papers with at least one of the following keywords: ERC, ERCs, earnings response coefficient, and earnings response coefficients. The paper must also be an archival paper and have at least one regression of returns on earnings surprises. This resulted in a total of 34 papers reviewed. Of the papers reviewed, all papers examine coefficients, and nine papers (26%) examine R-squareds.

Ahmed (1994)
Baik et al. (2022)
Bandyopadhyay (1994)
Billings (1999)
Chi and Shanthikumar (2017)
Core and Schrand (1999)
Core et al. (2002)
Cready et al. (2001)
Dechow and You (2012)
DeFond and Park (2001)
Dhaliwal and Reynolds (1994)
Ettredge et al. (2005)
Fang et al. (2017)
Ferri et al. (2018)
Francis et al. (2002)
Geng et al. (2023)
Gu and Xue (2008)
Hayn (1995)
Imhoff and Lobo (1992)
Jame et al. (2016)
Kallapur (1994)
Kerstein and Kim (1995)
Kothari and Zimmerman (1995)
Lipe et al. (1998)
Lobo et al. (2017)
Nelson et al. (2008)
Orpurt and Zang (2009)
Penman (1992)
Soo and Soo (1994)
Teets and Wasley (1996)
Teoh and Wong (1993)
Tucker and Zarowin (2006)
Williams (2015)
Wilson (2008)

Appendix B.

Table A1. Variable Definitions.

Variable	Definition
CAR[−1,+1]	Market-adjusted return during [−1,+1] days around the earnings announcement period
EARN_SURP	(Earnings—lagged earnings)/Market value of equity
REV_SURP	(Revenues—lagged revenues)/Market value of equity
CFO_SURP	(Cash flow from operations—Lagged cash flow from operations)/Market value of equity
ROA	Earnings/Lagged assets
SIZE	Market value of equity
BM	Book value of equity/Market value of equity
REV	Revenues/Lagged assets
CFO	Cash flow from operations/Lagged assets
AG	(Assets—Lagged assets)/Lagged assets
YEAR	Fiscal year
IND	Fama–French 48 industries

Notes

1. Dechow et al. (2010) note that investors respond to information that has value implications and that a stronger relation between value and earnings suggests earnings better reflect fundamental performance.
2. The literature commonly uses coefficients to examine the informativeness of earnings. For example, to examine whether the earnings of firms with Big N auditors are more informative, Teoh and Wong (1993) run regressions of earnings announcement period returns on earnings surprises and control variables and compare the coefficients on earnings surprises for firms with Big N auditors and firms with non-Big N auditors. Teoh and Wong (1993) find that the coefficient on earnings surprises is higher for firms with Big N auditors and conclude that earnings are more informative for such firms. More generally in the literature, the coefficients on earnings surprises in two groups of firms are compared, either through an interaction term or separate regressions, to assess whether earnings are more informative for a certain group of firms. See Appendix A for a list of papers reviewed.
3. These journals are selected based on the University of Texas, Dallas, UTD24 database of leading business journals. Future research could examine a broader set of journals to capture a more comprehensive view of the evolution and trends in the field.
4. Incremental R-squareds and incremental adjusted R-squareds are helpful in regressions with multiple independent variables (e.g., control variables) because they capture the incremental explanatory power of the variable of interest instead of the total explanatory power of all variables in the regression.
5. In this paper, *EARN_SURP* is calculated as the change in earnings deflated by the market value of equity. Because the market value of equity is the product of share price and number of shares outstanding, this is analogous to deflating surprise in earnings per share-by-share price, which is common in the literature (see Appendix A). Similarly, *REV_SURP* and *CFO_SURP* in this paper use the market value of equity as a deflator.
6. For regressions with controls, the R-squared and adjusted R-squared values for the regression do not change when examining *REV_SURP* and *CFO_SURP* compared to when examining *EARN_SURP* because they reflect the overall explanatory power of the regression.
7. Because there are no control variables, the incremental R-squared values are the same as the R-squared values, and the incremental adjusted R-squared values are the same as the adjusted R-squared values.
8. It may be possible for some small or negative coefficients to be insignificant. An additional (untabulated) analysis that examines only specifications that have coefficients with p-values below 0.10 reveals similar results. Disagreement is 21.3–21.4 percent for *EARN_SURP*, 15.5 percent for *REV_SURP*, and 15.3–16.8 percent for *CFO_SURP* without controls (corresponding to Table 5) and 18.0–36.2 percent for *EARN_SURP*, 28.0–43.4 percent for *REV_SURP*, and 40.0–50.0 percent for *CFO_SURP* with controls (corresponding to Table 7).

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